THINK: TOWARD PRACTICAL GENERAL-PURPOSE BRAIN-COMPUTER COMMUNICATION

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THINK: TOWARD PRACTICAL GENERAL-PURPOSE BRAIN-COMPUTER COMMUNICATION

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SUMMARY

In this work, we develop and present **THINK**, a practical general-purpose brain-computer communication platform that relies on the OpenBCI and OpenViBE hardware and software platforms, and uses Bluetooth LE for communicating out. Specifically, we consider the scenario where a subject is wearing a sensor array (an electrode cap), and consciously manipulating her thoughts (imagining limb movements) to communicate wirelessly with an external computing entity (a smartphone) without the aid of any external stimuli. **THINK** provides a secure, covert and non-intrusive channel for the users to communicate with the computers or the smartphones. THINK has a three-symbol sized vocabulary. It infers a '0' or '1' when the user imagines 'left' and 'right' limb movements respectively, and stays idle in the case of the 'rest' state. **THINK** relies on the 'mu' waves, which are known to present decrement in power of certain frequency bands. **THINK** is built as a general-purpose communication platform and can conceivably be linked to any application simply as an input mechanism.

Using **THINK**, we explore general aspects of brain computer communication that are application agnostic. In particular, we study the system accuracy and usability with real user experiments. The system accuracy was found to be highly variable across subjects and trials. We achieved a maximum accuracy of 83.4% and average accuracy of 53.4%. Even with low accuracy, we demonstrate that how is it possible to construct a successful BCC system. Further, in usability, we explore (i) how fast can the subject switch thoughts corresponding to symbols; (ii) is there an impact on accuracy with learning time; and (iv) how does accuracy drop with decreasing number of sensors (electrodes)? Using purely experimental analysis, we present some results that provide preliminary answers for these questions. We also provide motivation results for the future work in the context of (i) alphabet design as per user preference, and (ii) importance of pre-processing and requirement of better algorithms.

CHAPTER 1

INTRODUCTION

The brain is the seat of all human intelligence, cognition, and behavior [1]. Hence, for most of known history, humans have conceptualized, fantasized, and explored the notion of communication directly through thoughts in the brain [2]. With the discovery of electroencephalography (EEG) in 1929, obtaining a simple window into the functioning of the brain became a reality [3]. At a high level, any brain activity occurs through the synchronized electrical firing of millions of brain cells (neurons) communicating with each other. Such activity can be detected externally through appropriate sensors on the scalp on the brain that sense activity in specific portions of the electromagnetic spectrum (typically in the 0.5-100 Hz). Over the last century, there have been tremendous advancements into the understanding of which sections of the brain are responsible for what kinds of activities, in spite of there existing several aspects of the brain's functioning that are less understood or complete blind spots.

Having a window into the activities of the brain allows for both passive measurements (where the subject is not consciously manipulating the brain waves), and active measurements (where the subject is consciously thinking for the express purpose of manipulating the brain waves that are then picked up by external sensors). Within active measurements again, the synthetic thoughts of the subject can be aided by external stimuli (e.g. strobe light flashing at a certain frequency) or can be a function of purely the thought processes of the subject. *The context for this work is active measurements without any external stimuli.* We specifically consider the scenario where a subject is wearing a sensor array (an electrode cap), and consciously manipulating her thoughts to communicate wirelessly with an external computing entity (a smartphone) without the aid of any external stimuli (Fig. 1.1).

This is not the first work to explore such a scenario. There have been numerous efforts

Figure 1.1: A BCI user wearing an electrode cap[1]

over the last few decades to harness brain computer communication (BCC), especially for people with disabilities [4, 5]. The unifying thread across all such efforts though is the singular focus on enabling a very specific application of brain computer communication in each of the settings. The goal of this paper though is different. With the very recent advent of open brain computer interface (BCI) platforms and technologies, it has indeed become possible to consider BCC through a broader lens. *The focus of this work is to consider BCC as a general-purpose communication platform, and study certain key properties such as accuracy rate, think rate, learn rate, scalability, etc., in an application agnostic fashion.*

Briefly, we develop and present an experimental BCC platform called **THINK** that relies on two open platforms - OpenBCI and OpenViBE. **THINK** allows for BCC through the imagined movement of limbs, has a vocabulary size of $three$, and uses Bluetooth LE for communicating out.

THINK is built as a general-purpose communication platform and can conceivably be linked to any application simply as an input mechanism. We then use **THINK** to study generic properties of BCC such as the rate of accuracy, the rate at which symbols can be thought and hence communicated, and the impact of learning on the accuracy. We also consider some practical questions such as the accuracy to form-factor trade-off that could inform future practical BCC platform designs.

[1]Image source: `http://www.lce.hut.fi/research/css/bci/`

CHAPTER 2
BACKGROUND

The idea of communicating by mere thoughts has captured popular imagination for centuries. The experimental findings of Richard Caton in 1875 [6] confirming the presence of electrical activity in brain, promised its possibility in real-life. Biological signals of the brain are captured in the form of electric potentials and converted into digital commands, converting the much-imagined fantasy into reality. This riveting notion of information transfer between a brain and a computer, Brain-Computer Communication (BCC), enables one to interact directly with computer or smart devices, without the involvement of peripheral nerves and muscles. BCC achieves this by mapping the biological signals (brainwaves) to digital signals, establishing a direct non-muscular pathway between the brain and the computer. Knowledge of neuroscience, signal processing, pattern recognition and machine learning is collectively used in understanding the brainwaves to establish such mapping.

2.1 Brain Waves

The presence of billions of neurons in the brain and their inter-communication through electrical impulses forms the basis of cognition in humans. Chemical activities inside the neuron cell body and dendrites result in depolarization and hyper-polarization of the cell membrane resulting in the generation of electrical activity. Neurons located in different parts of the brain are associated with different functionalities respectively. The electrical impulses produced are meant for either processing or transmitting information to the specific body part responsible for that functionality. *The superposition of a large number of electric pulses results in the generation of brain waves*.

Brain waves can be observed by planting electrodes either inside the grey matter (invasive) or on the scalp (non-invasive). Electroencephalography (EEG) is one of the most

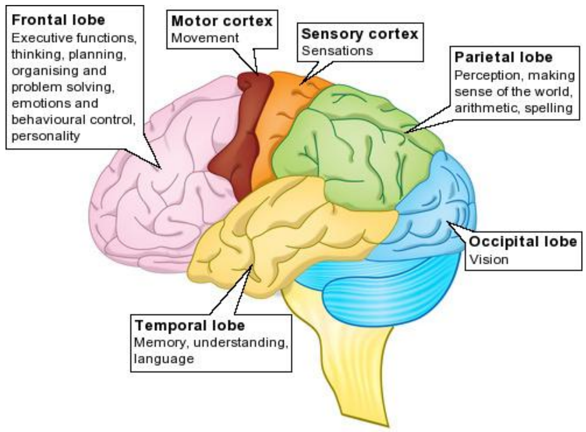


Figure 2.1: Different parts of the brain and their functionalities

widely used non-invasive methods to record electrical changes on the brain scalp. EEG cannot capture a single neuronic activity. Instead, it measures electrical activity of a group of neurons (typically millions). It is similar to observing a wave arriving at a shore after it was generated in the heart of the ocean. This electric activity is known to be heavily correlated with an individuals cognitive and physiological processes, according to the location of source neurons as shown in Fig 2.1. For example, electrical activity measured over the occipital lobe, represents the visual processing in humans.

EEG activity is generally measured in terms of frequency in *Hertz*. Brainwaves are categorized into six main categories according to the frequency bands. Each category (frequency band) has specific characteristics associated with different biological processes,

1. **Infra-Low (<0.5 Hz) :** The brain-waves with the time period in several seconds lie in this category, also emcompasses Slow Cortical Potentials (SCPs), originating from large cell assemblies in the upper cortical area. Increment in SCP negativity and positivity can be observed before and after epileptic seizures, respectively.

2. **Delta (0.5 - 4 Hz) :** Delta waves are known to have higher amplitudes. They are highly prominent during the deep sleep (stage 3 and stage 4), and the deepest level of meditation.

3. **Theta (4 - 7 Hz) :** Theta waves are more dominant in young age. In case of adults,

it is associated with drowsiness, light and hypnotic sleeping states.

4. **Alpha (7 - 14 Hz) :** Alpha waves are mainly generated from the occipital lobe during rest state .They have a very high SNR (Signal-to-Noise Ratio) when eyes are closed.

5. **Beta (15 - 30 Hz) :** Beta waves are *activity waves*. Increase in Beta activity indicates increase in alertness, cognitive activity, consciousness etc.

6. **Gamma (>30 Hz) :** They are very high frequency waves. They are believed to be associated with expanded consciousness, but with the current knowledge nothing can be said about them with confidence.

A successful brain-computer communication system can be designed by capturing EEG and relying on modalities including Visually Evoked Potentials (VEPs), Mu waves, P300 and Alpha rhythms. Of these, Mu waves and Alpha rhythms do not require any external stimuli. These modalities are elaborated in section 2.3. As Mu waves are also theoretically capable of larger vocabulary sizes (unlike Alpha waves that differentiate only between rest and active states), for the platform presented in this work, we rely only on detection and processing of Mu waves that are consciously manipulated by the subject through imagined limb movements.

2.2 Significance of Brain-Computer Interfaces

The human brain is considered as the most complex physical structure in nature. BCC provides a meticulous view of the complex processes and neuronal architecture inside the brain, and helps in unraveling its mystery by understanding its intricate functionalities, and responses to stimuli and cognitive processes. Major applications of BCC are centric to the fact that it operates through thoughts alone. This unique property of BCC opens several possibilities in the medical domain. Severely damaged motor, sensory and cognitive processes can be restored through neuro-prosthetics, allowing locked-in patients (suffering from ALS, paralysis, etc.) to communicate. It has also been shown to successfully restore vision, auditory and movement impairments. BCC opens a window into the brain, which can then be leveraged in determining healthy state of being; studying and curing various diseases including epilepsy and sleep disorders. For healthy individuals, the chief applications of BCC are for communication and control purposes, providing ease of access to users. It can be considered as a potential substitute for traditional Human-Computer Interaction (HCI) devices. BCC is arguably a better modality of communication for HCI applications because of the following reasons:

- **Non-intrusiveness:** BCC provides perhaps the most non-disruptive way for users to interact with smart devices. Unlike other modalities that require a conscious disruption of the users current activity to facilitate interaction, BCI provides a silent seamless channel, where the user could continue with her current activity, and still manage to accomplish the BCI interaction successfully. Consider this in a conversation between users Alice and Bob. If Alice wants to communicate with her smartphone as she is having the conversation with Bob, she may do so without overtly interrupting that conversation if BCI is available. This is in contrast to other modalities such as voice commands or gestures to.

- **Passive Intent:** Typical modalities for HCI rely on the user overtly expressing intent. For example, if gestures are used to communicate with a smart device, a user has to explicitly perform those gestures to accomplish the interaction. However, one of the interesting attributes of BCC is that it is capable of capturing passive intent at the very source of those intentions thought. In other words, applications relying on BCC can be built without ever requiring the users to overtly perform any active thinking, and instead simply tap into the natural thought processes of the users. For example, when a user naturally makes a mental note to remember to do an action in the future, the thought can be passively detected by the BCC platform and appropriate reminders put on the users calendar. One of the benefits of passive intent detection is that the burden is no longer on the user to actually remember to take actions.

- **Shortened intent to action pathway:** Current HCI modalities require users to actively perform certain muscular movements to map intentions to some intermediary steps, which are further translated into particular actions. BCC essentially skips the intermediary steps, and thus quickens the end-to-end process and requires a minimal amount of effort.

- **Privacy:** BCC provides the most secure communication channel for interaction i.e. it eradicates the possibility of leakage of thoughts while interacting. Since an eavesdropper would need to have physically proximate access to the brain signals, there is implicit physical-space security enabled by BCC. As an example, while typing in passwords is not safe if someone is looking at the keyboard, thinking the password through is considerably safer.

2.3 Related Work

The first Brain-Computer Interface (BCI) dates back to 1973, developed by Jacques Vidal to control the cursor movements. He used the expression for his research projects in UCLA [7, 8], funded by NSF and contracted by DARPA, which marked the beginning of research in BCI for communication and control.

The prominent electrophysiological signals used to design present BCI systems are, Visually Evoked Potentials (VEPs), Event Related Potentials (ERPs), Slow Cortical Potentials (SCPs) and sensorimotor rhythms, which are shown in Fig.2.2.

2.3.1 Visually Evoked Potentials (VEPs)

Stimulating a subjects central or peripheral visual field evokes large potentials in brain signals, dominant in occipital scalp area. It has been established that occipital brain frequency resonance with the frequency of visual stimuli, oscillating in a sinusoidal pattern.

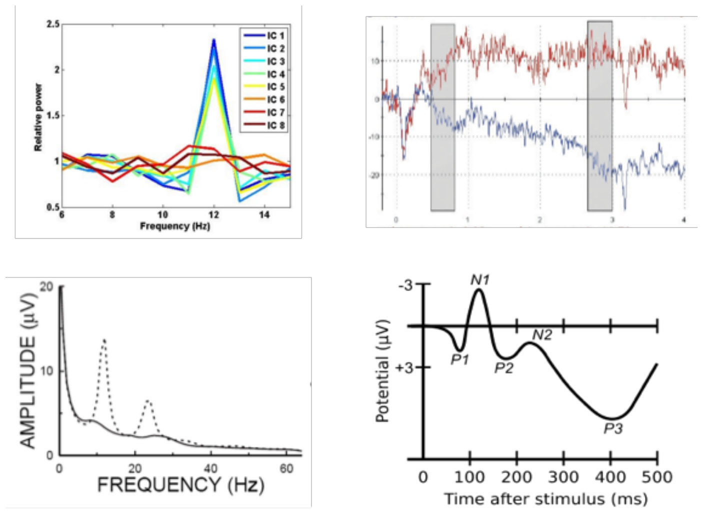


Figure 2.2: Top left figure shows power spectrum density when subject gazes at stimuli flickering with 12 Hz. Top Right figure shows the SCP production of positivity (red) and negativity (blue). Left bottom figure is the time-domain representation of mu-waves. Right Bottom figure depicts ERPs including P100,N1000,P200,N200 and P300.

These are further categorized into transient VEP (tVEP) and steady-state VEP (SSVEP) based on stimulus rates. Vidal developed a VEP based BCI which could move cursor on monitor screen by determining eye gaze direction of user [7, 8]. Brain Response Interface (BRI) developed by Sutter (1992) presented 8x8 grid of symbols and achieved rate of 10-12 words/min with high accuracy [9]. [10] designed a self-regulates BCI and achieved an accuracy rate of 92% with an avg. selection time of 2.1 seconds.

2.3.2 Slow Cortical Potentials (SCPs)

As evident from the name, slow cortical potentials are slow oscillations that could last upto 10s. SCPs are typically associated with cortical activation [11, 12, 13], which can be learnt to control with training procedures. Various Thought Translation Devices (TTD) were demonstrated on the basis of SCPs, extensively targeted for providing communication abilities to locked-in patients [14]. Similarly, SCP based BCI, Language Support Program (LSP) can write 2-36 words/hr with accuracy ranging from 65 to 90% [15].

2.3.3 Event Related Potentials (ERPs)

ERPs are behavioral responses of brain to specific events or infrequent/significant stimuli infused with regular stimuli in auditory, visual or sensory format. P300, a positive deflection after 300ms of stimuli, is predominantly used in several modern BCI designs. One of the famous P300 based BCI is, P300 speller, initially developed by Farewell and Donchin in 1988 with information rate of 5 letters per minute and improved further in upcoming years [16, 17]. A typical P300 speller presents 6x6 matrix of symbols flashing rows and columns with distinct frequency, requiring users to pay attention to particular symbol. N170 presents negative peak after 170ms correlated with facial visual stimuli, helpful in distinguishing cases of faces vs non-faces [18]. Similarly, other ERPs, namely N400, N300, P600 etc are associated with semantic congruity and language processing [19, 20].

2.3.4 Sensorimotor Rhythms (Mu waves)

Sensorimotor rhythms, also known as mu waves are EEG activities occuring over sensory and motor cortical areas of brain, in between frequency range of 8-12 Hz. They occur with actual or imagined body part movements, and are distinct in terms of spatial localization over primary motor and sensory cortex of brain, mapped directly to motor and sensory body parts [21, 22]. The Wadsworth BCI is based on same signals, which require users to imagine limb movements in order to control a cursor on 2-D screen. The system achieving information bit rate of 20-25 bits/s [23] requires elongated training and hectic in terms of use operations. Mu-waves based BCIs are particularly favoured as they dont present strict requirement to external stimuli. [24] explores the similar problem to facilitate communication based on thoughts itself.

Here, in our work we put an effort to realize BCI as a potential substitute of current HCI systems. We pondered over issues that are highly critical in installing BCI for daily use like effect on performance of higher think rate, selection of electrodes and individual training.

CHAPTER 3

BCI PLATFORMS

Pertaining to very slow data rates of developed BCI technology, BCI has always been considered for medical purposes targeting locked-in individuals or disable users suffering from various neuromuscular disorders. Over the past few years, focus of BCI research widely expanded to include improved communication and HCI experience for healthy users. The increasing demand of BCI research in seemingly every aspect of human life, and rising interest in wearable technology, puts a need for compact and affordable non-invasive solution to acquire and process brainwaves simultaneously.

There are three main components of a BCI system, an electrode sensor array placed on the scalp, a hardware platform to digitize crude brainwaves, and an algorithmic processing platform to interpret brain waves. Scalp electrodes provide conductive medium for brainwaves to reach hardware interface. Active electrodes comprises of in-built circuitry for electric current amplification, resulting in improved signal quality as compared to passive electrodes. Typically, electrode arrays (a set of electrodes) are positioned over a cap or in the form of a wearable headset. In the terms of their ease of use, dry electrodes are preferred over wet ones, but they are more prone to noise and present reduced signal quality of brainwaves [25]. Absence of robust and high-performance dry sensor technology which could possibly reduce setup time, maintenance and user discomfort, proves to be a bottleneck step in realizing our goal of deploying BCI in day-to-day life.

The second and most important component is signal amplifier, which amplifies and digitizes these itty-bitty EEG signals captured from scalp electrodes. Since Vladimir Pravdich-Neminsky published the first use of EEG in 1912 [26], numerous tools were developed to read brainwaves. Competition in corporate sector of BCI, launching innovative and advanced solutions, is impacting its development in accelerated manner. Emotiv EPOC+, Biopacs EEG Solution, g.BCIsys from gtec, OpenBCI and OpenEEG are few leading products for the same. We will discuss one such device, OpenBCI in the next subsection and its advantages over other such devices.

3.1 OpenBCI: The Hardware Platform

Joel Murphy and Conor Russomanno developed OpenBCI (Open Source Brain-Computer Interface) which is an open-source, low-cost, programmable interface to access raw EEG signals [27]. The interface has the capability to connect with upto 16 electrodes at a time, amplifying and digitizing the signals at 250Hz. It is built around Atmel ATmega microcontroller, which can be re-programmed on the board. The heart of the OpenBCI board is ADS1299, designed and manufactured by Texas Instruments [28]. It is a multi-channel, low-noise, 24-bit Analog-to-Digital Converter (ADC) specifically designed for EEG and similar biopotential measurements. It can also be used for measuring muscular and heart activity i.e. Electromyography (EMG) and Electrocardiography (ECG) respectively. The most recent version of OpenBCI i.e. v3, comes with RFduino and USB dongle which allows digitized EEG signals to transfer wirelessly to PCs, laptops, smartphones or any bluetooth compatible device. The installed RFduino is equipped with latest Bluetooth Low Energy (BLE) technology, which supports similar data rates as older version with reduced power consumption, making it last longer. OpenBCI board is also armed with SD card slot to store signal data in memory card for situations where instantaneous connectivity is not possible.

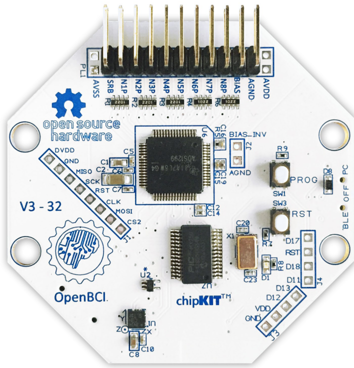
A lot of such hardware modules are available in current market but either they are very expensive, or perform poorly or provide restricted access to system design and raw EEG data. It is very crucial for research community to have all of the above features bundled in a single piece of hardware. What makes OpenBCI unique and suitable for our purpose, is its transparent design with full control over raw EEG signals as well as access to hardware architectural design and underlying algorithms for translating EEG signals to meaningful data, which can be expanded or modified further to suit our needs. OpenBCI comes with Brainwave Visualizer written in Java, C++ and Python. It can be used to simultaneously visualize time-domain EEG signals, their frequency spectrum and spatial power localization.

The final component in designing BCI system is a software processor which performs spatial and frequency filtering, artifact removal, feature extraction and learning, to map high-resolution complex EEG signals to trivial outputs. Publically available major software platforms are BCI2000, OpenViBE, EEGLAB, BCILab, out of which we discuss OpenViBE in next subsection.

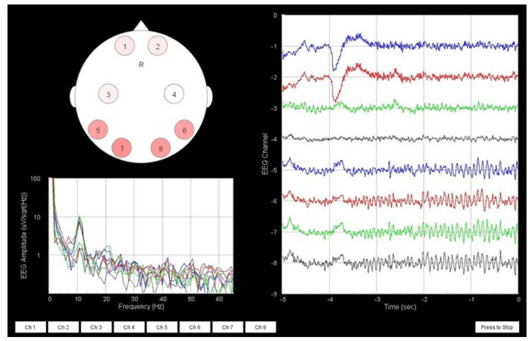
3.2 OpenViBE: The Software Platform

The software counterpart of our research project is OpenViBE developed by Inria, INSERM and Orange Labs [29]. It is a free software distributed under an open-source license, for designing, testing and using BCIs. It can acquire, filter, process, classify and display EEG data in real-time environment. Its open-ended design and availability of numerous data acquisition drives allows it to directly interact with any BCI system including OpenBCI.

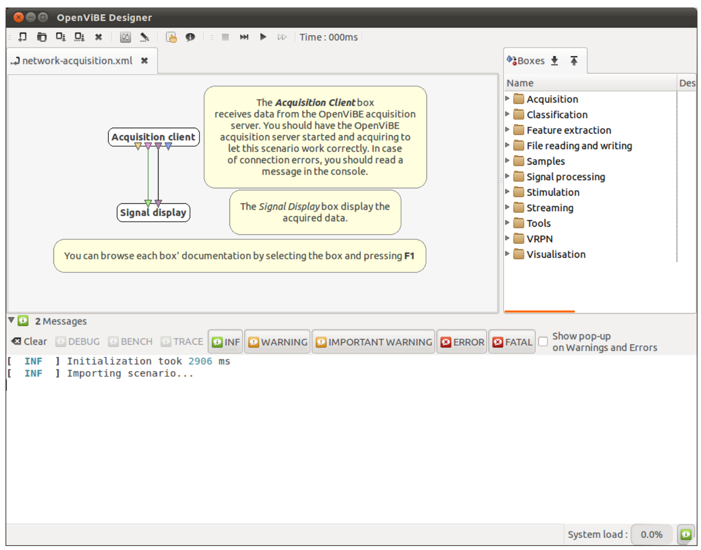
OpenViBE is written in C++, compatible for both windows and linux environments. It comprises of numerous software modules devoted to data acquisition, algorithms for signal filtering, digital signal processing, machine learning, pattern recognition and data visualization, which can be interconnected to design a BCI software paradigm. Software users without any programming experience can design successful BCI system, using its graphical user interface without even writing a single piece of code. It has abstract and categorized representations of all software algorithms. Researchers and programmers can even modify the code or develop such software blocks by their own to add more functionality in their BCI design. It can interact with various high-end Virtual Reality (VR) applications, which



(a) OpenBCI Board



(b) Brainwave Visualizer



(c) OpenViBE User Interface

Figure 3.1: BCI Platforms

makes this platform a top choice for neuro-game developers. Pre-configured scenarios for multiple BCI paradigms are present in openViBE including motor imagery design, P300 speller etc. to get a head start in designing BCI systems.

CHAPTER 4

THE THINK PROTOTYPE

The goal of this work is to develop an interface to control handheld mobile devices via thought alone. **THINK** serves as a communication interface between the 'Human' and the 'Machine' with a vocabulary size of 3 ('Left', 'Right', 'Rest'). It transmits binary data (0 or 1) when the subject imagines the lifting of the 'Left 'or the 'Right' hand respectively. In 'Rest' state i.e. no imagination of limb movements, the system remains in idle state and does not initiate any data transfer. While exploration of a larger vocabulary size is out of scope for this work, we choose a vocabulary size of 3 for its balance of simplicity and usability (e.g. the system can support simple directives such as 'yes/no/no operation', 'left/right/no operation', etc.).

THINK is based on active measurements of the brain waves as the user consciously tries to manipulate the waves to effect control. The core mechanism behind **THINK** is motor imagery, since it does not require any external visual stimuli to operate and users can voluntarily control the system. **THINK** requires the user to wear an electrode-cap attached with the OpenBCI board, which is further connected to a smartphone over Bluetooth link[1]. The current prototype uses CAP-100C (by BIOPAC Systems Inc.) and 32-bit OpenBCI board. The OpenViBE application resides on an Internet server and receives raw EEG signals, processes them and labels them as one of the states out of 'Left', 'Right' and 'Rest' as depicted in Fig.4.1. The corresponding decoded state is transmitted as necessary to the smartphone on the same network through a vanilla TCP/IP session. The Smartphone application then displays the decoded state on the mobile screen. However, an observant reader would realize that the system can be modified to allow it to drive other third-party

[1]Productized versions of the system can be more elegant and practical in terms of form-factor. We study the dependency on the number of electrodes to this effect later in the paper.

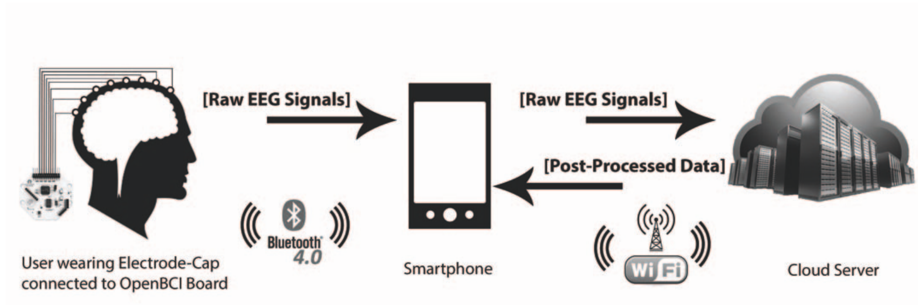


Figure 4.1: Workflow of **THINK** Prototype

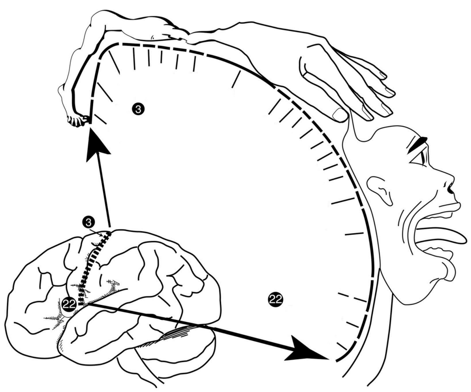


Figure 4.2: Motor Cortex and Cortical Homunculus

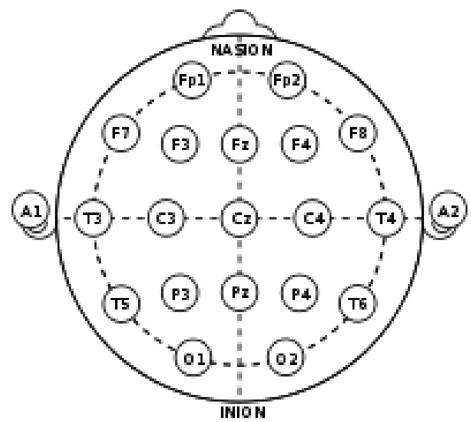


Figure 4.3: International $10-20$ System

applications as well (for e.g. gaming, connecting and disconnecting incoming calls).

4.1 Motor Imagery: The Backbone

An Internally or externally paced event leads to a change in EEG activity in the form of event-related synchronization (ERS) or desynchronization (ERD). ERS[30] and ERD[31] are characterized by an increase and decrease in the power spectrum of particular frequency bands respectively. *Mu and central beta rhythms display attenuation in power (a typical ERD) during imagination of specific limb movements [32].* These ERDs present contralateral spatial localization i.e. imagination of movement on the right side of the body is captured in the left hemisphere of the brain and vice-a-versa. The mu-rhythms are specifically localized over the motor and sensory areas of the brain, and hence are known as sensori-

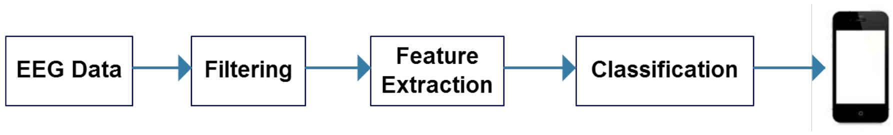


Figure 4.4: Signal Processing Architecture of **THINK** in OpenViBE

motor rhythms. A mapping of the primary motor cortex and the primary somatosensory cortex in the brain to motor and sensory body parts is illustrated in the *cortical homunculus* diagram shown in Fig.4.2. Left and Right hand movements are primarily concentrated over C4 and C3 positions respectively according to the international $10-20$ system shown in Fig.4.3. The basic idea behind **THINK** is to acquire mu waves over the appropriate areas of scalp, and process them to find ERD, thus detecting user imagination.

4.2 Signal Processing

For the signal processing component of **THINK**, the motor imagery scenarios present in OpenViBE are modified to suit the system requirements. Fig.4.4 depicts the signal processing chain of **THINK** in OpenViBE. Briefly, the processing functions are as follows:

1. **EEG Data:** Raw EEG data is acquired at the acquisition server running independently on an Internet server. A *VRPN server* or *OpenBCI driver* can be used to stream raw EEG data in real-time.

2. **Filtering:** The received EEG signals are digitally filtered in the 8-30 Hz band that includes Mu and central beta rhythm frequencies. The frequency filtered signals are allowed to pass through a *CSP Spatial Filter*. The *CSP Spatial Filter* generates new output channels by applying a linear combination to input channels (8-channels in this case) such that the variance for one class is maximized while at the same time the variance for the other class is minimized. The coefficient of the *CSP Spatial Filter* is learned by performing offline training sessions. Having a CSP filter helps in transforming the data as to reduce the noise power from the signal.

3. **Feature Extraction:** As ERD is evident in the power spectrum, we generate an epoch of past one second and calculate the total power of signal by performing summation of squared amplitudes. We repeat this every 1/16th of a second (i.e. 16 times a second) to enable real-time detection. A signal epoch of the past one-second is generated every 1/16th of a second. This average power of epoch signals is stored as hand-crafted features.

4. **Classification:** Finally, the features are classified into one of three categories ('Left', 'Right', 'Rest') using a Linear Discriminant Classifier (LDA). In the final design, the classification is a two-step process. First, the features are classified into "Movement" and "Non-Movement (or Rest)" category. If it results in "Movement" category then the features are further classified into 'Left' and 'Right' classes. Otherwise, they are declared as 'Rest' class. In the "Movement" category itself, if the probability for decoded 'Left' and 'Right' classes is less than the preset threshold value, they are again labeled as belonging to the 'Rest' class to boost the system accuracy (and thus, the system design is little biased towards the 'Rest' category). We've experimented with different scenarios for the classifier design, and we concluded the above mentioned designed gives best results.

5. **Connecting with Smartphone:** The decoded states from OpenViBE are finally sent to the smartphone through a TCP/IP session. The smartphone application plays the role of a client role and simply displays the result periodically. We've implemented the application on Android platform, which gathers the final results (requires the server on the same network) and displays the result on Android phone in real-time

CHAPTER 5

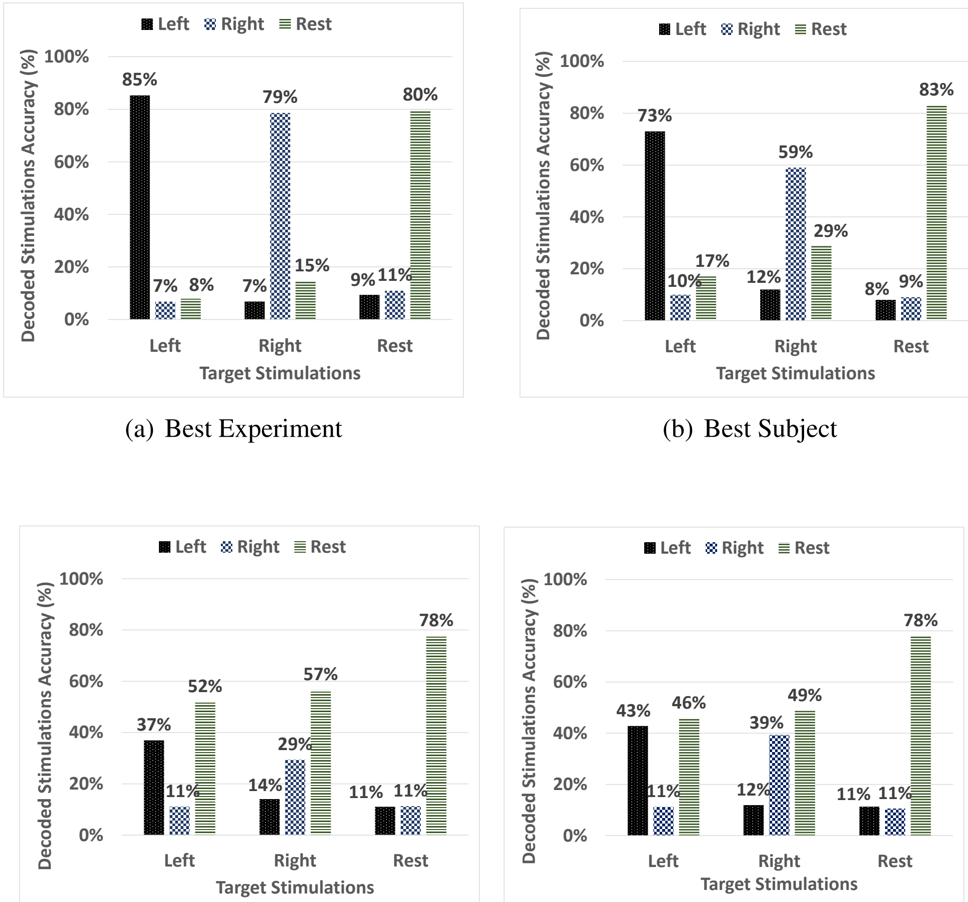
EXPERIMENTAL ANALYSIS

With **THINK** as our experimental platform, we perform real-user studies to evaluate the systerm performance and usability. Further, with the collected data we also present motivational results for the future work in the same context.

Experimental Methodology

We studied eight subjects through trials that each lasted 11 minutes and 30 seconds. Each trial starts with the presentation of a fixation cross at the center of the monitor screen. After 3 seconds, a red arrow appears that indicates the corresponding stimulation cue. Users are required to imagine the lifting of limbs in order to initiate data transfer ('Left' and 'Right' red arrows corresponded to 'Left' and 'Right' limb movement imagination, and 'Up' corresponded to the 'Rest' state). Such is made possible by modifying the 'Graz Motor Imagery BCI Stimulator' ([29]) lua script to display 'Left', 'Right' and 'Rest' stimulation cues to the subject.

THINK is capable of capturing different types of movements with different body parts, in this work we only evaluate **THINK** for the particular limb movements (Lifting of Left/Right hand). One experimental run consists of randomized distributed 30 'Rest' stimulation cues and 15 cues each for 'Left' and 'Right'. The rest of the settings are kept to the default values as in the script. During the imagination task, subjects were asked to remain motionless. The wireless data-rate of the system was measured to be approximately 64.45 Kbits/s. No optimization of this communication overhead was performed although there is scope for the same. The EEG Data was sampled using Biopac's CAP100C over T3, F3, F4, C3, C4, Cz, P3 and P4 positions according to the international $10 - 20$ system at 250 Hz. The ground and bias electrodes were attached to the left and right ear lobes respectively. The



(a) Best Experiment (b) Best Subject

(c) Worst Subject (d) All Subjects

Figure 5.1: Accuracy Measure

system is fully functional on its own without any requirement of external stimuli. External stimulations are used to evaluate the system performance.

Data is recorded in such fashion over a course of 5 days per subject. Each day included two sessions for the same subject. The recorded raw EEG data is further processed offline to evaluate the system usability and overall performance.

5.1 System Performance: Accuracy

Fig.5.1 shows the confusion matrix (where each row represents the predicted class while the columns represent the instances of actual class) for target and decoded stimulations in a graphical form for (a) best experiment, (b) best subject, (c) worst subject, and (d) all

Table 5.1: Accuracy Metric

	Best Exp.	Best Subject	Worst Subject	All Subjects
Correct Classification	81.2%	72.3%	47.9%	53.4%
Mis Classification	11.3%	12.5%	15.9%	15%
Neutral Classification	7.5%	15.2%	36.2%	31.6%

subjects. The 'best experiment' results show the performance for the best individual trial (Fig.5.1(a)) across all subjects. Out of the total of 80 trials (8 subjects, twice a day for 5 days), an average of 10 trials for each subject is calculated, and the best and the worst performances amongst the subjects are presented in Fig.5.1(b) and Fig.5.1(c) respectively. Fig.5.1(d) presents the averaged performance across all 80 trials. For the best experiment, the system outputs 85% of time correct stimulations for 'Left' cue, 79% for 'Right' and 80% for the 'Rest' cues. We define the accuracy measure using three different quantities which are presented in Table 5.1.

1. **Correct-Classification:** Counts all target stimulations that were decoded correctly.

2. **Misclassification:** Stimulations corresponding to the following target-decode pair, *'Left' to 'Right'* or *'Right' to 'Left'* or *'Rest' to 'Left/Right'*. This quantity hurts the performance of the system.

3. **Neutral-Classification:** Counts instances when 'Left' or 'Right' target stimulations are decoded as 'Rest'. This reduces the data rate of the system by keeping system in idle state when a transmission is intended.

For the best experiment, the three defined accuracy measures are 81.2%, 11.3% and 7.5% in order.

A relatively large variation in the accuracy measures for different subjects across different experiments can be observed in Fig.5.1. The averaged correct classification accuracy obtained for best subject, worst subject and all subjects is 72.3% , 47.9% and 53.4% respectively , which is significantly lower compared to the highest (81.2%) indicating a large variance value. Even with the 53.4% accuracy rate, a practical system can be realized as misclassification occurs only 15% of the time (the rest of the errors are due to the Neutral-Classification (31.6%) status that simply lowers the data rate of the system.). Note that a completely random decision process would have an accuracy rate of 33%.

> The system accuracy is highly dependent on the user's performance. Among all experimental trials, the accuracy metric attained a maximum of 81.2%. The same metric turns out to be 53.4% if averaged for all trials. Even a low accuracy rate (53.4%) is sufficient for practical BCC systems as long as there are few misclassifications (15%) occurring in the system.

5.2 System Usability

5.2.1 Learn Rate

In this section, we evaluate the effect of training on individual's performance. Eight different subjects were studied twice a day over a course of five days. Their correct classification accuracy was averaged for each day and reported in Fig.5.2. It should be noted that these experimental runs did not involve providing of any kind of neurofeedback (a technique for training of brain) to the users.

From Fig.5.2, we can see that although performance metric improves for subject S2, S3 and S6 but there is no fixed pattern for the other users. Accuracy for subject S7 lies in 65%-80% block and rest of the subjects lies in 40%-60% block. From this, we can conclude that the mu-rhythms are indeed characteristic property of different individuals.

Evaluation of impact of biofeedback on learning rate would be part of our future work. We

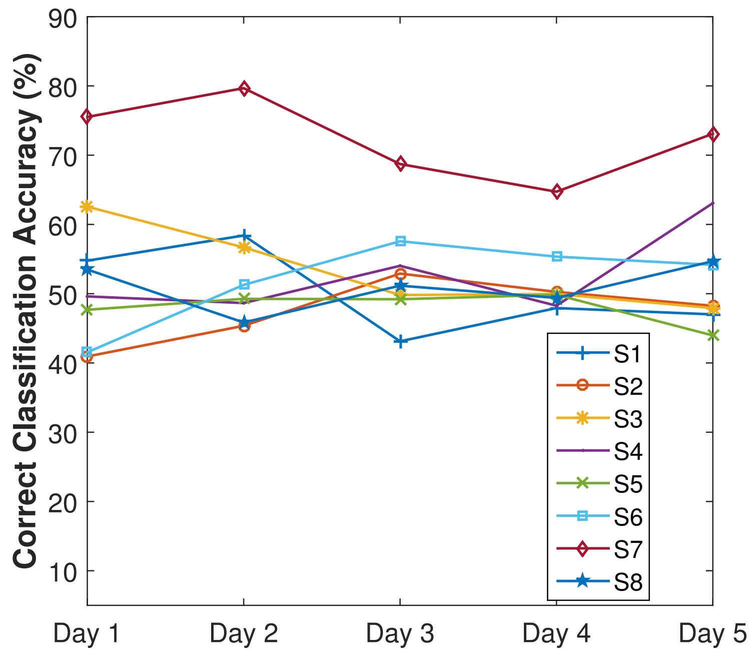


Figure 5.2: Learn Rate

plan to design a system that can learn classification parameters simultaneously with allowing user to adapt to the system during experiment.

There is no considerable effect of training on learn rate without biofeedback. Performance for S7 varies in 65%-80% range while rest of the subjects lies in 40%-60% range, indicating mu-rhythms as characteristic property of an individual.

5.2.2 Think Rate

This particular experiment investigates the system performance as the time between thinking states is varied. *Think duration* is defined as the period of time a user is required to imagine the limb movements. This quantity controls the data rate of the system and could be impactful in developing a practical BCC system.

For the experiments, the *Think duration* was varied from 4 down to 0.5 seconds. It was not reduced below 0.5 seconds due to practical issues with a human responding to a fleeting

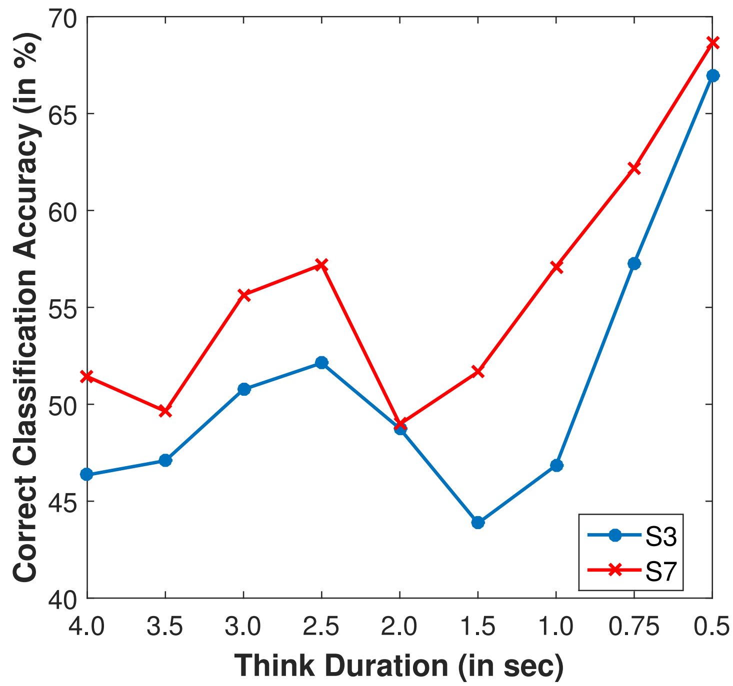


Figure 5.3: Think Rate

stimuli. Experimental results were calculated keeping the epoch rate fixed to 0.25 seconds and the results are plotted in Fig. 5.3 for subjects S3 and S7. We observe that the performance metric increases with a decrease in the think duration. The performance curve increases from 46.1% to 66.9% and 51.4% to 68.6% in case of S3 and S7 respectively, accounting nearly 20% increment in the correct-classification accuracy in both the cases. An explanation for this trend is that subjects usually tend to think moving limbs for a fixed amount of time even if the stimuli duration is longer due to focus issues. Hence, all averaged signal epochs would not necessarily contain corresponding stimuli features resulting in mislabeling of data and a dip in performance for the longer think durations.

An additive increment of 20% is obtained in the system accuracy when the think duration is reduced from 4 seconds to 0.5 seconds. This enables the system to be more accurate when run on the faster think rates.

Table 5.2: Electrode Selection for Best Performance

Electrode Count	Electrode Combination
2	C3,C4
3	C3,C4,Cz
4	C3,C4,Cz,F4
5	C3,C4,Cz,T3,F3
6	C3,C4,Cz,P4,F4,T3
7	C3,C4,Cz,F43,P4,F3,T3
8	C3,C4,Cz,P3,P4,F3,F4,T3

5.2.3 Number of Electrodes

The form-factor of the electrode cap is a direct function of the number of electrodes required. Hence, the total number of electrodes and their selection are key aspects in designing BCC systems. Fig.5.4 presents the best and the worst obtained classification accuracies when the electrode count is varied from 2 to 8. The best and worst case scenarios are identified after a brute-force search of all possible accuracies with a given electrode count. The accuracy increases from 66.19% to 79.24%, and attains steady state afterwards. This shows that only 3 electrodes are sufficient if chosen optimally. Table 5.2 presents the best combination of electrodes against the electrode count. ‘C3’, ‘C4’ and ‘Cz’ being substantial positions in motor imagery context are subsets of electrode-sets for higher number of electrodes.

An exponential increase can be noticed for the worst case scenario with increasing number of electrodes, ranging from 33.33% to 82.39%. The considerable gap between the worst and best performance curves highlights the importance of electrode selection.

$Three$ electrodes are sufficient to design a practical system with accuracy up to 79.24%. The performance metric varies from 36.52% to 79.24% depending on the approach for electrode selection.

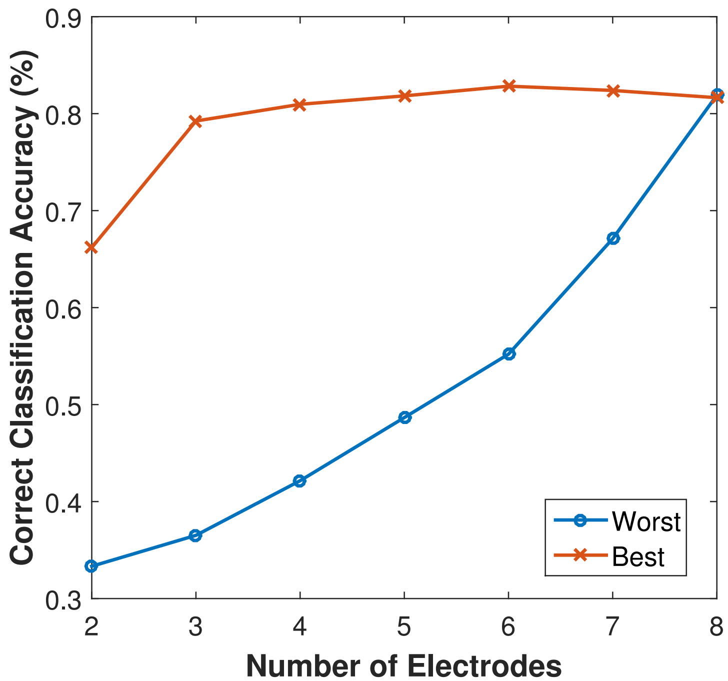


Figure 5.4: Number of Electrode

Table 5.3: Accuracy difference over “Left” and “Right” alphabets

	Accuracy Difference	Character Preference
Subject 1	25.96%	“Left”
Subject 2	40.14%	“Left”
Subject 3	19.54%	“Left”
Subject 4	9.65%	“Right”

5.3 Motivation Results for the Future Work

5.3.1 Alphabet Design

One of the key challenges for the wide-spread adoption of the BCC is the difficulty of the users in learning to generate EEG commands for communicating through the modulation of their EEG signals. It has been shown that some of the users have significant difficulties in using BCC systems. This phenomenon that is known as BCC-illiteracy [33, 34] is rooted in the underlying neurophysiological and cognitive processes that involve generating stable neural representations for the EEG-generated alphabets [35]. There are certain biomarkers of EEG that may be used to predict users performance [33].

In the context of BCC, along with the inherent predilection of the user, the characteristic properties of brainwaves also play a significant role in accuracy. We demonstrate this idea by comparing the accuracy of “thinking left” vs. “thinking right” for a set of 4 subjects (Table 5.3). We observed an accuracy improvement of 19.54% while choosing “Left” alphabet as compared to “Right” alphabet in case of Subject 3 (In this case “Left” accuracy was 72.53% and “Right” accuracy was 60.67%). On the other hand for subject 4, there was a 9.65% improvement in accuracy while choosing “Right” alphabet over “Left” alphabet. Though anatomy of the body structure is same for right or left, but preferred usage of one hand (from childhood) and mu-waves characteristics can result in significant difference in accuracy.

5.3.2 Importance of Pre-Processing

The EEG raw data obtained from sampling scalp electrodes is strife with noise and represents a myriad of conscious and subconscious processes. Despite the recent advances in machine learning, the importance of data pre-processing still remains high. Data pre-processing involves an array of operations that either suppresses or enhances the features in the context of the application task and the ML pipeline. In EEG signals, the ML algorithms fail to perform well if fed with irrelevant and redundant information (along with noise and unreliable data).

To demonstrate the importance of pre-processing of the EEG data before feeding it into the ML algorithms, we present a comparison of accuracy (Table 5.4) of the previously discussed experiment with and without the pre-processing stages. In the above analysis, for computing the accuracy ”without pre-processing” we skip the temporal and spatial filtering stages, and allow the raw data to directly enter the feature extraction and Linear Discriminant Analysis (LDA) stages. As we can see from the above results, without pre-processing

Table 5.4: Accuracy with and without pre-processing

	Accuracy with pre-processing	Accuracy without pre-processing
Subject 1	50.91%	33.40%
Subject 2	72.34%	34.59%
Subject 3	53.38%	34.42%
Subject 4	51.98%	33.46%

the accuracy drops down to a random baseline accuracy (vocabulary size: 3). The classifier is not able to learn any relevant information about classes due to very low Signal-to-Noise Ratio (SNR). Well-known techniques from literature spans time-frequency filters [36], spatial filters [37], adaptive filtering [38], genetic algorithms [39], Wavelet transformation [40], Common Average Reference (CAR), Surface Laplacian (SL) to the dimensionality reduction and Blind Source Separation (BSS) techniques i.e. PCA [41] and ICA [42] respectively [43]. However, pre-processing architectures in their current state-of-the-art forms are not adaptive i.e. designed specifically for particular situation or class of brainwaves (P300[44], Epilepsy, artifact removal etc.).

CHAPTER 6
CONCLUSION

6.1 Challenges and Perspectives

Although we have come very far in terms of our progress in developing BCI systems, but still we have miles to go before realizing a fully functional BCI system that can be deployed in day-to-day life. There are several challenges for accomplishing this dream, inter-related to biomedical, neurological, signal processing and machine-learning domain which will be discussed in this section.

- The foremost problem lies in understanding the enigmatic structure of the brain itself. Until we know the origin and cause of all waves coming to shore, it is really difficult to infer much information from them. An insight on background processes occurring in brain, their cause and effect on brain waves is vital.

- Providing ease of access to users is a crucial concern for BCI developers. Inconvenience in wearing wet electrode sensors and pain involved especially when using technology for long hours should be ideally minimized. Comfortable wearables are being launched in market based on dry sensing technology but they are currently suffering with low performance and reliability issues.

- Small vocabulary size and low data rates are that paramount reasons that BCI systems are not very common among able beings. Till date, only P300 based BCI systems are able to simulate vocabulary of 26 alphabets but they suffer from low data rate. Larger vocabulary size and faster decision rates are mandatory to cope up with the pace of modern world.

- Combination of multiple brain modalities of brain waves ex. VEPs, alpha rhythms could prove beneficial in having BCI systems with wide perception of users thinking. For instance, possibly combining active and passive thinking will not only boost system performance but would be helpful in gaining background insights.

6.2 Conclusion and Future Work

This work considers the potential of BCC as a general-purpose substitute for current Human-Computer Interaction Systems. We demonstrate that a simple motor imagery scenario can improve the communication experience of users with a machine whether it be a smartphone, a tablet or a laptop. The accuracy results obtained through the experimental runs is promising enough to advance research in the field. BCC has historically been considered for the challenged and disabled people and EEG has been looked at for medical purposes only. We believe that the presented **THINK** platform and the associated experimental analysis serve as a valuable starting point for several new research directions in the area of brain-computer communication. We studied the general aspects of BCC using **THINK**, specifically, (i) what is the accuracy of the system? (ii) how fast can the subject switch thoughts corresponding to symbols; (iii) is there an impact on accuracy with learning time; and (iv) how does accuracy drop with decreasing number of sensors (electrodes)? We also provided motivational results for the future work, including, selecting alphabets as per users' preferences (to boost the per user accuracy), and establishing the importance of pre-processing algorithms for machine learning (posits requirement of better pre-processing).

There are a slew of challenges that we will explore as part of future research, including the following: (i) how large can the vocabulary size be for practical brain-computer communication? (ii) can other modalities of brain waves (e.g. VEPs, alpha rhythms, etc.) be used in tandem with Mu waves for better performance? (iii) what are the usability issues (e.g. wet vs. dry electrodes, perceived appearance when wearing electrode cap) with brain-computer communication systems? and (iv) how intense and in what form does training need to be to elicit better accuracy rates?

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